SLAM-Based Spatial Memory for Behavior-Based Robots

Shu Jiang* Ronald C. Arkin*

**School of Interactive Computing, Georgia Institute of Technology, Atlanta, GA 30308, USA*
e-mail: {sjiang, arkin}@ gatech.edu

Abstract: Knowledge is essential for an autonomous robot to act intelligently when tasked with a mission. With recent leaps of progress, the paradigm of SLAM (Simultaneous Localization and Mapping) has emerged as an ideal source of spatial knowledge for autonomous robots. However, despite advancements in both paradigms of SLAM and robot control, research in the integration of these areas has been lacking and remained open to investigation. This paper presents an integration of SLAM into a behavior-based robotic system as a dynamically acquired spatial memory, which can be used to enable new behaviors and augment existing ones. The effectiveness of the integrated system is demonstrated with a biohazard search mission, where a robot is tasked to search and locate a biohazard within an unknown environment under a time constraint.

Keywords: Simultaneous Localization and Mapping, Behavior-Based Robotics, C-WMD Missions

1. INTRODUCTION

Knowledge is essential for any intelligent entity to not only survive, but thrive, in the natural environment. Reactive robotic systems have found tremendous success without explicit knowledge representation by tightly couple sensing to action to produce timely response in dynamic and unstructured environments. However, the source of reactive systems' success is simultaneously their source of limitation; that is, applications of reactive robotic systems are limited by their lack of internal knowledge representation (Mataric, 1992). While there is a common consensus on the importance of knowledge for robotic systems, how it should be represented and used within these systems remains open to investigation. Furthermore, care needs to be taken when adding knowledge representation to reactive robot systems, since knowledge, if misused, could interfere with the simplicity and efficiency of reactive control (Arkin, 1998).

Arkin (1998) presented some examples of spatial knowledge integration for behavior-based robots, which resulted in more flexible and general navigation. These examples include behavioral memory (Balch & Arkin, 1993), where world knowledge was incorporated as spatial memory that is local to a specific behavior, and long-term memory maps (Mataric, 1992), where world knowledge was integrated as long-term topological maps for navigational path planning. With recent advancements, the paradigm of SLAM has emerged as an excellent source of spatial knowledge for autonomous robots. However, while major progresses have been made in the respective areas of SLAM and robot control, surprisingly, their integration has not been fully investigated (Milford & Wyeth, 2010; Song et al., 2014).

This paper presents the integration of SLAM with a behavior-based robotic system as a dynamically acquired spatial memory to enable more general and intelligent behaviors than their pure reactive counterparts, while at the same time maintaining the reflexive nature of reactive systems. The motivation is to leverage current advancements in the SLAM paradigm to enable robot behaviors that can be used to achieve complex missions. The integration of SLAM into a behavior-based system occurs at two basic levels: 1) at the system level, where the output of the SLAM module (i.e., map and robot pose) is made accessible to all primitive behaviors and 2) at the behavioral level, where a perceptual schema turns the SLAM output into information that is required for the individual behavior to generate its response. This results in a robotic system where the integrated SLAM-based spatial memory can not only be used to enable new behaviors but to augment existing ones as well.

A biohazard search mission, where a robot is tasked to search for a biohazard in an unknown environment under a time constraint, is presented to illustrate the effectiveness of the integrated system. The mission is motivated by the unfortunate threat of terrorist attacks using WMD (Weapons of Mass Destruction) (Dickinson, 1999), which robotics has been identified to play a key role in defense against (Doesburg & General, 2004). Experimental trials of the biohazard search mission demonstrate the effectiveness of the SLAM-based behaviors in enabling a robot to take advantage of the integrated spatial knowledge to act intelligently in an unknown environment while being responsive to its surroundings.

The remaining sections proceed with a review of knowledge integration for robotic systems with a focus on SLAM-based spatial knowledge in Section 2. We then follow, in Section 3, with a description of the integration of a SLAM system with a behavior-based robotic framework. The effectiveness of the integrated system is then demonstrated with experimental trials, where SLAM-based behaviors are used to accomplish a Counter-WMD mission, which is described in Section 4, along with experimental results in Section 5. Section 6 concludes the paper and proposes future work.

2. RELATED WORK

A reactive robotic system's action is tightly coupled to its sensory inputs to produce timely reaction in dynamic and unstructured environments. Reactive systems generate fast responsive actions by avoiding the use of explicit representational knowledge (or world model). However, the lack of knowledge poses limitations on the ability of these systems to carry out complex missions. Several researchers have addressed this issue by integrating world knowledge into robotic systems for intelligent navigation behaviors that addresses various issues encountered in pure reactive navigation. Arkin (1998) presented a comprehensive survey of these systems, which demonstrated the usefulness of knowledge integration for reactive systems.

Motivated by the observation that reactive systems have been limited to applications requiring no explicit internal representation, Mataric (1992) presented an integration of a topological map representation into a reactive, subsumption-based mobile robot. The goal of the integration is to maintain a map of the environment and use it for path planning. Fox et al. (1998) integrated data derived from a previously acquired map of the environment as a "virtual sensor" with real sensors for collision avoidance. The objective is to ensure safe operation within an environment with large number of ill-shaped obstacles (e.g., humans) that could be problematic for purely sensor-based methods (Fox et al., 1998). To enable a robot to solve complex navigation problems such as the box canyon, Balch and Arkin (1993) integrated a local spatial memory into a reactive robotic system. The spatial memory, inspired by ants leaving chemical trails behind them as they travel, is a 2D array of integers where each element of the grid records the number of times the corresponding square patch in the world has been visited. This spatial memory enabled an "avoid the past" behavior for robot navigation that allows the robot to avoid areas that have already been visited. However, the spatial map becomes inaccurate as the robot moves about the world.

Recent advancements in the paradigm of simultaneous localization and mapping (SLAM) (Durrant-Whyte & Bailey, 2006; Thrun & Leonard, 2008) have made it an excellent source of spatial knowledge for mobile robots. However, as Milford and Wyeth (2010) argued, the fields of SLAM and robot control have made tremendous advancements "in parallel with little overlap". This "little overlap" occurs in the paradigm of integrated exploration (Makarenko et al., 2002; Sim & Roy, 2005) and active SLAM (Kim & Eustice, 2013; Leung et al., 2006; Stachniss et al., 2004), or SPLAM (simultaneous planning, localization, and mapping) (Leung et al., 2008), which concerns itself with the integration of exploration, planning, localization, and mapping. The objective of integrated exploration and active SLAM is to get an accurate map efficiently. The basis of the methods to realize this objective comes from the insight that the quality of map is highly dependent on the sequence of motion/path executed by the robot. For instance, Kim and Eustice (2013) and Stachniss et al. (2004) presented active SLAM strategies that actively close loops during exploration and mapping, where utilities associated with the exploratory and revisitation actions are used to determine whether to keep exploring or to revisit past locations.

Thus, the problem of integrated exploration and active SLAM can generally be viewed as a trajectory planning problem that tries to optimize, or balance the tradeoffs among, some utility measures (e.g., map coverage and accuracy) of the SLAM task. Makarenko et al. (2012) presented a strategy for integrated exploration that evaluates alternative actions based on information gain, localization quality, and navigation cost. Leung et al. (2006) formulated the active SLAM problem as an optimal trajectory planning problem that tries to maximize map coverage and minimize map uncertainty. Bourgault et al. (2002) maximized the accuracy of the map building process during exploration by adaptively selecting control actions that maximize the localization accuracy. Specific metrics for quantifying the uncertainty of the robot pose and the generated map, such as a-optimality (Sim & Roy, 2005) and d-optimality (Carrillo et al., 2012), have been used by motion planning algorithms to plan a multi-step trajectory for active SLAM. However, the paradigms of integrated exploration and active SLAM focus on the task of exploration for the purpose of generating accurate map rather than using the spatial knowledge that SLAM provides to accomplish tasks beyond mapping.

Besides calling to attention the lack of overlap between the paradigms of SLAM and robot control, Milford and Wyeth (2010) presented the integration of SLAM with a hybrid robot control architecture, which was then used to perform a delivery task within an office environment. The SLAM algorithm (i.e., RatSLAM) generates an experience map, which is a semi-metric topological graph map that consists of nodes called experiences and links between these experiences. Similar to active SLAM approaches, the experience map is better suited for planning robot motion than for reactive behaviors. Furthermore, similar to some active SLAM approaches (Bourgault et al., 2002; Leung et al., 2006; Makarenko et al., 2002), Milford and Wyeth (2010) maintains a local obstacle map, for local path planning, in addition to the experience map generated by the SLAM module.

In conclusion, while various representations of world knowledge have been integrated into reactive robotic systems for intelligent navigation behaviors, SLAM has emerged in recent years as an important alternative source of spatial knowledge for autonomous robots. While the information provided by SLAM has been used for trajectory/path planning to solve active SLAM problems (Carrillo et al., 2012; Leung et al., 2006) and an office delivery task (Milford & Wyeth, 2010), the SLAM-based spatial knowledge has not been fully exploited by robotic systems to enable more comprehensive intelligent reactive behaviors. Thus, this paper investigates the question of how SLAM algorithms can be integrated into a behavior-based robotic system to enable intelligent reactive robot behaviors while at the same time maintaining the responsiveness of reactive systems.

3. SPATIAL MEMORY AND ROBOT BEHAVIORS

Acquisition and representation of spatial knowledge is one of the foundations of intelligent mobile robots. Recent advancements in the SLAM problem have made it an important tool for acquiring and representing spatial knowledge within robotic systems. This section presents the integration of SLAM with a behavior-based system as a dynamically acquired world model that enables more general and intelligent robot navigation techniques than using immediate sensory information alone, while at the same time maintains the responsiveness of reactive systems. The goal is to leverage current advancements in SLAM algorithms to achieve more intelligent and general reactive robot behaviors for critical missions such as those encountered in C-WMD scenarios.

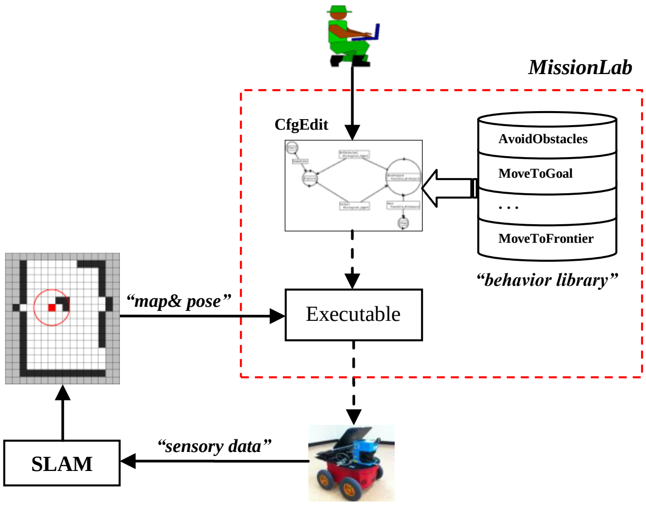


Fig. 1. Integration of SLAM and *MissionLab*

The integration of SLAM with *MissionLab*, a behavior-based robot programming environment (MacKenzie et al., 1997), is illustrated in Fig. 1. *MissionLab* provides a usability-tested graphical configuration editor (Endo et al., 2004), CfgEdit, where a mission operator can design the robot behavior for a given mission in the form of a finite state automaton (FSA). Through a graphical editor, the operator has access to a library of pre-existing behaviors (e.g., *GoToGoal*) that can be used to construct the robot behavioral FSA. The SLAM algorithm used for the integration is GMapping, a Rao-Blackwellized particle filter-based approach for learning grid maps (Grisetti et al., 2007). The output of the SLAM algorithm is an occupancy grid map of the environment along with the robot's pose within it. An occupancy grid is a metric map where each grid cell has a value corresponding to the probability that the cell is occupied (Elfes, 1989). Other similar SLAM algorithms could also be integrated.

The integration of SLAM into *MissionLab* occurs at two basic levels: 1) the system level, where the output of the SLAM module is made accessible to all behaviors and 2) the behavioral level, where perceptual schemas turn the SLAM output into information that are required for the behaviors to generate their responses. At the system level, the output of the SLAM module (i.e., map and robot pose) acts as a spatial memory of the environment that is dynamically acquired as the robot experiences the world. At the behavioral level, a perceptual schema is embedded within each behaviour that turns the spatial memory into the information that is required for the behavior to generate a response to the world (Arkin, 1990). Each perceptual schema, follows the principle of action-oriented perception, produces only the information that is necessary for the particular behavior (Arkin, 1990). When the resulted system is tasked with a mission, SLAM executes concurrently with active robot behaviors. The mapping is proactive in the sense that the map is built as the robot moves within the environment; and the process of mapping and localization is synchronized with robot behaviors through sensory update it receives from the robot.

While the spatial memory is global in the sense that it is accessible to all behaviors within *MissionLab*, how the knowledge is used depends upon each specific behavior. First of all, the spatial memory can be used to augment pre-existing behaviors that reside in a library within *MissionLab*. This usage is illustrated with *AvoidObstacles*, a pre-existing reactive behavior in *MissionLab* that moves the robot away from obstacles detected through sensors. The most straightforward way to augment the behavior with spatial memory is to replace the stimulus input (e.g., laser sensory data) with the spatial memory (i.e., the occupancy grid map) and modify the perceptual schema for the behavior to turn the dynamically acquired world model into necessary percept for the motor schema to generate the output vector for the motor response.

The modified perceptual schema for the AvoidObstacles behavior, *pseudo-laser*, is implemented through beam tracing within the map to generate pseudo laser scans of the environment. Each occupancy grid cell within a sphere of influence would generate a repulsion vector for the robot. This sphere of influence (illustrated as red circle in Fig. 2) can be used to constrain the generation of repulsion vectors to occupancy grids that are in the proximity of the robot. Motor schema of the behavior remains the same as the pre-existing obstacle avoidance behavior (Balch & Arkin, 1993), which computes a repulsion vector from each obstacle reading. The repulsion vectors are then summed and normalized to generate a resultant repulsion vector to drive the robot away from obstacles.

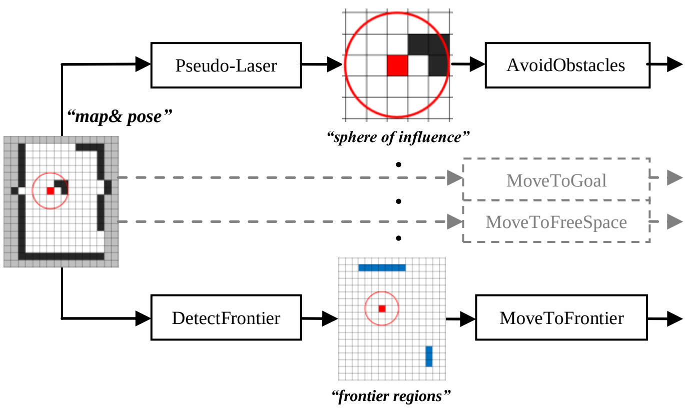


Fig. 2. Illustration of SLAM-based Behaviors

Other behaviors can be augmented by the spatial memory in a similar fashion. For instance, with spatial memory, the *MoveToFreeSpace* behavior can take into account free spaces that are beyond the robot's immediate sensory range. Furthermore, the localization of a robotic system is generally improved by the pose estimate provided by the SLAM-based spatial memory. The *MoveToGoal* behavior is especially sensitive to the localization accuracy of the robot when moving to a goal location. By using the pose estimate provided by SLAM, the performance of *MoveToGoal* behavior can be improved over dead-reckoning with odometry.

Secondly, the integrated spatial memory can enable the creation of new navigational behaviors that are more intelligent and efficient than using immediate sensory data alone. To illustrate, we implemented a *MoveToFrontier* behavior based on Yamauchi's frontier-based approach for autonomous exploration, which explores an unknown environment by moving toward the frontiers of a dynamically generated map (Yamauchi, 1997). Yamauchi defined frontier as the boundary between the open and unknown spaces within an occupancy-grid map. This resulted in a behavior that drives the robot to the areas that the robot will gain the most new information about the unknown environment by moving toward a frontier. Given an occupancy grid map, a perceptual schema for the behavior identifies the frontier cells through a process similar to edge detection in image processing. The motor schema for this behavior then selects a frontier to move toward among the candidate frontiers. Two simple methods for selecting the frontier to move to are: 1) closest-frontier – the robot moves to the closest frontier and 2) largest-frontier – the robot moves to the largest frontier.

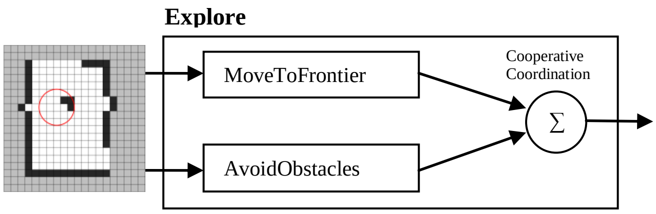


Fig. 3. Behavioral Assemblage for the *Explore* Behavior

MoveToFrontier alone is not sufficient for a robot to effectively explore an unknown environment since it drives the robot toward a frontier without any regard for potential obstacles that might be in the path. However, by combining the *AvoidObstacles* and the *MoveToFrontier* behaviors via a coordination mechanism (e.g., cooperative coordination) within *MissionLab* (Fig. 3), we obtain a higher level exploration behavior that enables the robot to explore an unknown environment using the frontier-based exploration strategy while avoiding obstacles simultaneously. Fig. 3 shows the behavioral assemblage of the *Explore* behavior whose output is a normalized weighted sum of the constituent behaviors.

4. C-WMD MISSIONS

Terrorist attacks using weapons of mass destruction (WMD) is not a question of "if" but "when" (Dickinson, 1999). Thus, the development of countermeasures to these attacks is essential for safeguarding the security and safety of societies under the threat of terrorism. Attacks using biological weapons should be of most concern since they are characterized by "maximum destructiveness and easy availability" (Betts, 1998; Henderson, 1999). With these scenarios in mind, we present a biohazard search mission to illustrate the effectiveness of integrated SLAM-based spatial memory in enabling a robot to carry out Counter-WMD type missions. The biohazard search mission entails a robot being tasked to search for and locate a biohazard with undisclosed location within an unknown environment.

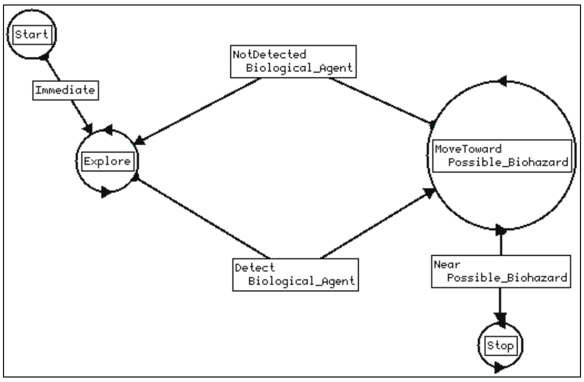


Fig. 4. Behavioral FSA for the *Biohazard Search* Mission

The strategy for biohazard search in an unknown environment consists of two basic steps: 1) explore the environment and 2) move toward the biohazard once it is detected. This strategy is instantiated in MissionLab as a finite state automaton (FSA) (Fig. 4), with the behaviors we introduced based on the integrated SLAM-based spatial knowledge in the previous section. The robot FSA for the biohazard search mission consists of a set of behaviors (i.e., *Explore* and *MoveToBiohazard*) and triggers (i.e., *Detect* and *NotDetected*, and *Near*). With this FSA, the robot starts with exploring the unknown environment with the frontier-based exploration behavior, *Explore*. If a biohazard is detected during exploration, the robot would transition to the behavior of moving toward the biohazard. However, while moving toward the biohazard, if the biohazard is not detected anymore, the robot's behavior would transition back to exploration of environment; this could be caused by initial false positive of the presence of the biohazard. Thus, the robot needs to move within a certain radius (e.g., 1.5m) of the biohazard to ensure accurate detection of the biohazard, at which point the search mission is considered completed.

Fig. 5. Robot and Biohazard

The robot used for this mission is a Pioneer 3-AT as shown in Fig. 5. The robot is equipped with a laser scanner for sensing of the environment and acts as an input to the SLAM module. A forward-facing camera on the robot is for biohazard detection. The biohazard is represented by a red bucket with the biohazard symbol and strapped to a toy explosive device with a countdown counter (Fig. 6). Color and shape features of the biohazard bucket are used for biohazard detection. Color and shape features of the biohazard bucket are used for biohazard detection. The *MoveToBiohazard* behavior utilizes the centroid of the detected blob to navigate toward the biohazard and uses the size of the shape feature to determine its relative distance.

a) A relatively "open" environment

b) A relatively "cluttered" environment

Fig. 6. Operating environments

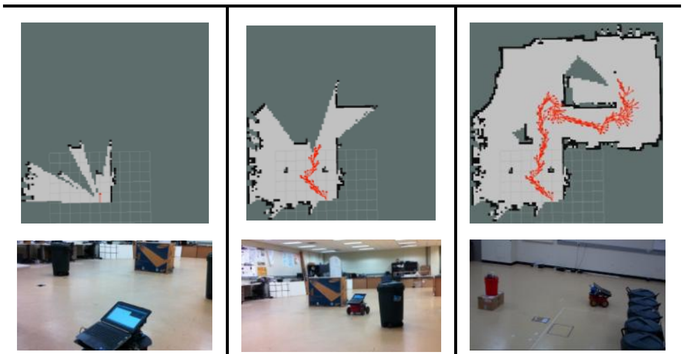
To illustrate the effectiveness of the SLAM-based behaviors, we conducted experiments where the biohazard search mission is carried out in two environments with different degrees of complexity. The operational environments of the biohazard search mission are shown in Fig. 6. We start with a rather benign environment where the biohazard is located in a relatively "open" area without any obstruction (Fig. 6a). The second environment (Fig. 6b), is a relatively "cluttered" environment where the biohazard is in an area partially cornered off by makeshift walls.

The goal of the robot is to find the biohazard within each environment using the behavioral controller specified in Fig. 4. Performance of the biohazard search mission depends on the exploration strategy that is employed. The frontier-based exploration behavior is compared to a naïve pure reactive exploration behavior, *Wander*, which generates a random movement vector for the robot to explore an environment and uses the immediate sensory data (i.e., laser and odometry) for obstacle avoidance and localization. Furthermore, as we pointed out in the previous section, the perceptual schema for the frontier-based exploration behavior generates a number of frontiers. Thus, two simple methods for selecting which frontier the robot should move to are compared as well: closest-frontier versus largest-frontier.

In short, we conducted a 2x3 experiment with two environmental conditions (i.e., "open", "cluttered") and three exploration strategies (i.e., random, closest-frontier, largest-frontier) for the biohazard search mission. The biohazard search mission is executed 10 times with the robot operating at 0.1m/s for each combination of environment and exploration strategy. The start location of the robot and biohazard location stay the same across trials. For each trial, the mission completion time is recorded as the performance measure of the mission since time performance is of major concern for C-WMD missions.

5. RESULTS

Figure 7 shows snapshots of an experimental run of the biohazard search mission with the robot being guided by the largest-frontier-based exploration strategy. The robot starts the mission with no a-priori knowledge of the environment (Fig.7a). The map of the environment is built incrementally by the integrated SLAM system as the robot moves around in the environment (Fig.7b) Frontier regions of the map are extracted continuously as the map evolves; and the *MoveToFrontier* behavior generates a movement vector that drives the robot toward the largest frontier. The map information is also used by the *AvoidObstacles* behavior to prevent the robot from running into obstacles by generating repulsion vectors. When a biohazard is detected by the robot's onboard sensor, it moves toward the biohazard to ensure reliable detection (Fig.7c).



a) Robot starting the search mission | b) Robot navigating among obstacles | c) Robot moving toward biohazard

Fig. 7. Snapshots of a robot conducting the biohazard search mission

During the experimental trials, we observed that frontier-based behavior has a tendency to move the robot toward the center of an open space and away from obstacles during exploration, except when a frontier lies near or behind obstacles. An instance of this tendency is shown in Fig. 8, where a frontier caused the robot to immediately start moving toward the space between obstacles, at the initial stage of the mission. While the obstacles in the vicinity of the robot, as seen in Fig. 8, had an effect in forming the frontier regions, they did not influence the trajectory of the robot (just yet) since they were still outside the sphere of influence of the *AvoidObstacles* behavior. Thus, the robot's trajectory toward the center of the open space between obstacles was only influenced by the frontier. This general tendency of the robot to move toward the center of an open space can be attributed to the fact that the *MoveToFrontier* behavior drives a robot toward the center of a frontier region, which always lies between obstacles (i.e., occupied grid cells). This demonstrates that, with the integrated spatial memory, the reactive *MoveToFrontier* behavior is able to act intelligently without deliberative path planning, which has previously been a common approach for implementing frontier-based exploration (Holz et al., 2010; Yamauchi, 1997).

Fig. 8. Robot moving toward a frontier through open space between obstacles

Even when the robot is moving toward a frontier that lies near or behind obstacles, the robot is able to safely negotiate the environment with the spatial memory alone (i.e., without immediate sensory data from the laser). In Fig. 9, we observed that the robot is able to safely move away from the makeshift wall based on the information provided by the integrated SLAM-based spatial memory. However, using the spatial memory alone for safety-critical behaviors such as *AvoidObstacles* is not recommended. We only do so here to demonstrate that the behavior-based robotic system is able to maintain its responsiveness with the integration and usage of the SLAM-based spatial knowledge. As Arkin (1998) has cautioned, knowledge needs to be used with care. Relying too heavily on the spatial knowledge alone can be dangerous when there are errors in the knowledge. Furthermore, the integrated spatial memory is not able to handle dynamic environments since the underlying SLAM algorithm (similar to other conventional SLAM algorithms) has the assumption that the environment is static (Bailey & Durrant-Whyte, 2006). Thus, in practice, spatial memory should be used in conjunction with immediate sensory data for safety-critical behaviors.

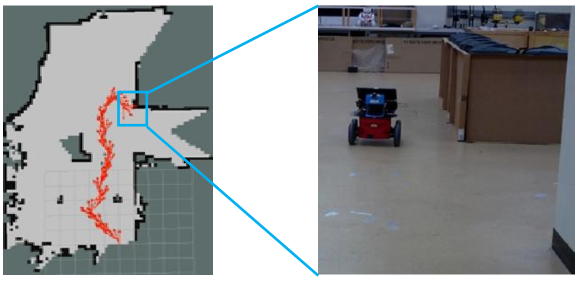


Fig. 9. Robot avoiding the makeshift wall

Table I shows the time performance of the robot in carrying out the biohazard search mission in two different environments with three different exploration strategies. The result is also visualized in Fig. 10. As expected, the time it takes the robot to finish the mission is longer for more complex environments, and the random exploration strategy performed the worst in both environments. In the "open" environment, while the performance of largest-frontier is significantly better than random strategy (with a t-test p-value = 0.02 < 0.05), the improvement of closest-frontier strategy over the random strategy is not statistically significant (p-value = 0.11 > 0.05). Thus, in the context of a biohazard search mission, the largest-frontier-based exploration strategy should be used if we have some a-priori knowledge that the operating environment has relatively large free spaces (e.g., warehouses). Furthermore, the performance of largest-frontier strategy in the "open" environment is also the most consistent with the smallest standard deviation of only 4.9 seconds. This consistency is useful when a mission needs to be executed multiple times where there is a tight tolerance in performance variation; and it also provides the mission operator a certain amount of confidence in predicting the performance when the mission need to be conducted in a different but similar environment.

Table 1. Biohazard Search Mission Completion Time

Exploration Strategy	***"Open" Environment***		***"Cluttered" Environment***	
	Mean (sec)	**SD (sec)**	**Mean (sec)**	**SD (sec)**
Random	398.0	264.1	> 900	N/A
Closest-Frontier	258.7	22.7	405.0	58.5
Largest-Frontier	185.9	4.9	371.9	68.7

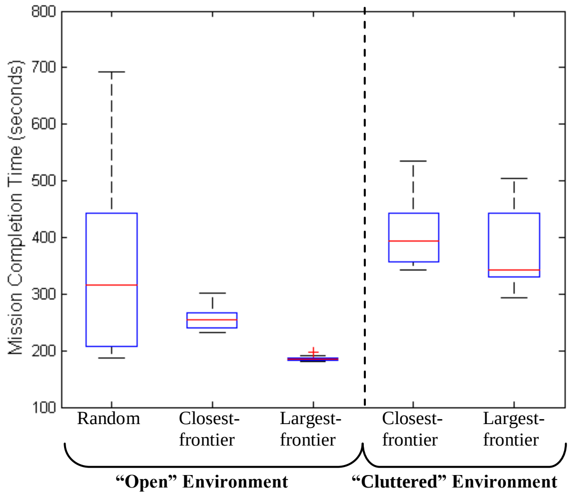


Fig. 10. Boxplots of Mission Completion Time Datasets for Different Exploration Strategies in "Open" and "Cluttered" Environments: *1) random strategy in "open" environment has the largest spread in its dataset, 2) largest-frontier strategy in "open" environment has the smallest spread in data, reflecting its consistent time performance, 3) both frontier-based strategies took longer to complete the mission in "cluttered" environment, 4) the ranges of mission completion times for closest-frontier and largest-frontier strategies overlap significantly in the "cluttered" environment, reflecting their insignificant difference, and 5) the largest-frontier strategy performs significantly better than the closest-frontier strategy in the "open" environment*

Moreover, while the SLAM-based search behavior was able to find the biohazard successfully in both environments, the search behavior based on the pure reactive behavior was not able to successfully find the biohazard in the "cluttered" environment under the mission terminal time of 15 minutes (900 seconds). Therefore, the pure reactive random search behavior is not suitable for missions, particularly time-critical missions, operating in cluttered environments (e.g., an office floor). The results also show that while the frontier-based exploration behavior using the largest-frontier mechanism to select the next frontier for the robot to move to performs significantly better than other strategies in the "open" environment the advantage of largest-frontier over closest-frontier selection method is not significant in the more complex "cluttered" environment. The improvement of largest-frontier over closest-frontier selection method is only 8.2% (p-value = 0.26 > 0.05) in the "cluttered" environment. Whereas the largest-frontier-based search behavior is 28.1% more efficient than closest-frontier-based search in the simpler "open" environment (p-value = $1.07 \times 10^{-8} \ll 0.05$). Despite the fact that we did not find a significant advantage of largest-frontier strategy over the closest-frontier strategy, in practice, the largest-frontier strategy should still be used for search type missions since the unknown operating environment could either be relatively "open" or "cluttered".

6. CONCLUSIONS

This paper presented an integration of SLAM into a behavior-based robotic system as a spatial memory with the goal of enabling intelligent robot behaviors while maintaining the responsiveness of reactive systems. The effectiveness of integrated system is illustrated with a biohazard search mission, where a robot successfully completed the mission using the behaviors that are enabled and augmented by the SLAM-based spatial memory. The experimental results demonstrated the potential of the spatial memory in enabling intelligent reactive robot behaviors for C-WMD type missions. Specifically, we have shown that with SLAM-based behaviors: 1) the robot was able to search an unknown environment intelligently without deliberative planning, 2) the robot was able to carry out a biohazard search mission more efficiently than using pure reactive behaviors, 3) the responsiveness of reactive systems was maintained with the integration and usage of the spatial knowledge, and 4) the largest-frontier-based exploration strategy outperformed the closest-frontier-based strategy in a relatively "open" environment, but has no significant advantage in a relatively "cluttered" environment.

The behaviors for exploration of the unknown environment used only the spatial memory, without immediate sensory data, for generating motor responses. However, this is for experimental purposes, and in practice immediate sensory data (e.g., laser range sensors) should be used in conjunction with the spatial memory for safety-critical behaviors to prevent catastrophic failure in case of error in the spatial memory. Furthermore, while the robot was able to conduct an informed search of the biohazard with the *MoveToFrontier* behavior, we have not yet taken full advantage of the integrated spatial memory. For instance, current SLAM-based behaviours do not reason over the uncertainty of the SLAM state vector. Thus, future work needs to expand the space of SLAM-based behaviors to realize the full potential of the integrated system.

While this paper focused on reactive behaviors and integrated a SLAM algorithm that generates a metric map (i.e., occupancy grid), SLAM algorithms (Grisetti et al., 2010; Kaess et al., 2008) that generate a topological map can be integrated in a similar fashion for more deliberative behaviors (e.g., planning). Furthermore, the SLAM-based behaviors are limited to environments with static obstacles since the SLAM algorithm incorporated is not able to deal with dynamic environments due to the underlying assumption that the environment is static. This is also a limitation of current SLAM approaches. However, solutions to the problem of SLAM in dynamic environments are being actively pursued. Thus, the integrations of SLAM algorithms for deliberative behaviors and dynamic environments are a natural extension to our present work.

Moreover, the experimental demonstration of the integrated systems is limited to simple environments. The scalability of the system depends on two factors: 1) the scalability of the SLAM algorithm, which has been demonstrated in (Grisetti et al., 2007), and 2) the scalability of the behavior. For reactive behaviors that only use local information (e.g., *AvoidObstacles*) the computation time stays constant independent of the map size; while for behaviors that require reasoning over the global spatial memory, the scalability would depend on the scalability of the underlying perceptual and motor schemas.

As we have indicated earlier, robotics has been identified as an important tool for safeguarding societies from attacks with WMD. However, failures of C-WMD missions can have disastrous consequences. Thus, a C-WMD mission, such as the biohazard mission, needs to be verified to have a certain level of performance guarantee before execution. While our research group has presented methods (Lyons et al., 2014; Lyons et al., 2012; Lyons et al., 2013) for verification of robot behaviors, the integrated SLAM-based behaviors presented in this paper presents a new challenge of verifying robot behaviors that are based on probabilistic algorithms such as SLAM. Thus, additional future work is to verify a C-WMD mission (e.g., biohazard search) where SLAM-based behaviors are used.

ACKNOWLEDGMENT

This research is supported by the United States Defense Threat Reduction Agency (DTRA), Basic Research Award #HDTRA1-11-1-0038.

REFERENCES

Arkin, R.C. (1990). Integrating behavioral, perceptual, and world knowledge in reactive navigation. *Robotics and autonomous systems, 6*(1), 105-122.

Arkin, R.C. (1998). *Behavior-based robotics*: MIT press.

Bailey, T., & Durrant-Whyte, H. (2006). Simultaneous localization and mapping (SLAM): Part II. *IEEE Robotics & Automation Magazine, 13*(3), 108-117.

Balch, T., & Arkin, R.C. (1993). Avoiding the past: A simple but effective strategy for reactive navigation. *IEEE International Conference on Robotics and Automation*.

Betts, R.K. (1998). The new threat of mass destruction. *Foreign Affairs*, 26-41.

Bourgault, F., Makarenko, A.A., Williams, S.B., Grocholsky, B., & Durrant-Whyte, H.F. (2002). Information based adaptive robotic exploration. *IEEE/RSJ International Conference on Intelligent Robots and Systems*.

Carrillo, H., Reid, I., & Castellanos, J.A. (2012). *On the comparison of uncertainty criteria for active SLAM.* Paper presented at the IEEE International Conference on Robotics and Automation (ICRA).

Dickinson, L.E. (1999). Military Role in Countering Terrorist Use of Weapons of Mass Destruction: DTIC Document.

Doesburg, M.J.C., & General, C. (2004). The Evolution of Chemical, Biological, Radiological, and Nuclear Defense and the Contributions of Army Research and Development (pp. 28): NBC Report, the United States Army Nuclear and Chemical Agency, Fall / Winter

Durrant-Whyte, H., & Bailey, T. (2006). Simultaneous localization and mapping: part I. *Robotics & Automation Magazine, IEEE, 13*(2), 99-110.

Elfes, A. (1989). Using occupancy grids for mobile robot perception and navigation. *Computer, 22*(6), 46-57.

Endo, Y., MacKenzie, D.C., & Arkin, R.C. (2004). Usability evaluation of high-level user assistance for robot mission specification. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews,, 34*(2), 168-180.

Fox, D., Burgard, W., Thrun, S., & Cremers, A.B. (1998). A hybrid collision avoidance method for mobile robots. *IEEE International Conference on Robotics and Automation, 1998. , 2*, 1238-1243.

Grisetti, G., Kummerle, R., Stachniss, C., Frese, U., & Hertzberg, C. (2010). Hierarchical optimization on manifolds for online 2D and 3D mapping. *IEEE International Conference on Robotics and Automation (ICRA)*.

Grisetti, G., Stachniss, C., & Burgard, W. (2007). Improved techniques for grid mapping with rao-blackwellized particle filters. *IEEE Transactions on Robotics, 23*(1), 34-46.

Henderson, D.A. (1999). The looming threat of bioterrorism. *Science, 283*(5406), 1279-1282.

Holz, D., Basilico, N., Amigoni, F., & Behnke, S. (2010). Evaluating the efficiency of frontier-based exploration strategies. *ISR/ROBOTIK*.

Kaess, M., Ranganathan, A., & Dellaert, F. (2008). iSAM: Incremental smoothing and mapping. *Robotics, IEEE Transactions on, 24*(6), 1365-1378.

Kim, A., & Eustice, R.M. (2013). Perception-driven navigation: Active visual SLAM for robotic area coverage. *IEEE International Conference on Robotics and Automation (ICRA)*.

Leung, C., Huang, S., & Dissanayake, G. (2006). Active SLAM using model predictive control and attractor based exploration. *IEEE/RSJ International Conference on Intelligent Robots and Systems*.

Leung, C., Huang, S., & Dissanayake, G. (2008). Active SLAM in structured environments. *IEEE International Conference on Robotics and Automation*.

Lyons, D.M., Arkin, R.C., Jiang, S., Harrington, D., & Liu, T.-M. (2014). Verifying and Validating Multirobot Missions. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*.

Lyons, D.M., Arkin, R.C., Nirmal, P., & Jiang, S. (2012). Designing autonomous robot missions with performance guarantees. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*.

Lyons, D.M., Arkin, R.C., Nirmal, P., Jiang, S., & Liu, T.-M. (2013). A Software Tool for the Design of Critical Robot Missions with Performance Guarantees. *Conference on Systems Engineer-ing Research (CSER'13)*.

MacKenzie, D.C., Arkin, R.C., & Cameron, J.M. (1997). Multiagent mission specification and execution *Robot colonies* (pp. 29-52): Springer.

Makarenko, A.A., Williams, S.B., Bourgault, F., & Durrant-Whyte, H.F. (2002). An experiment in integrated exploration. *IEEE/RSJ International Conference on Intelligent Robots and Systems*.

Mataric, M.J. (1992). Integration of representation into goal-driven behavior-based robots. *IEEE Transactions on Robotics and Automation,, 8*(3), 304-312.

Milford, M., & Wyeth, G. (2010). Hybrid robot control and SLAM for persistent navigation and mapping. *Robotics and Autonomous Systems, 58*(9), 1096-1104.

Sim, R., & Roy, N. (2005). Global a-optimal robot exploration in slam. *IEEE International Conference on Robotics and Automation (ICRA)*.

Song, J., Qiu, K., Gupta, S., & Hare, J. (2014). SLAM based adaptive navigation of AUVs for oil spill cleaning. *Oceans-St. John's*.

Stachniss, C., Hahnel, D., & Burgard, W. (2004). Exploration with active loop-closing for FastSLAM. *IEEE/RSJ International Conference on Intelligent Robots and Systems*.

Thrun, S., & Leonard, J.J. (2008). Simultaneous localization and mapping *Springer handbook of robotics* (pp. 871-889): Springer.

Yamauchi, B. (1997). A frontier-based approach for autonomous exploration. *IEEE International Symposium on Computational Intelligence in Robotics and Automation (CIRA'97)*.